A MODIFIED WEIGHT OPTIMISATION FOR HIGHER-ORDER NEURAL NETWORK IN TIME SERIES PREDICTION

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Special dedication to beloved family,

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ABSTRACT

Most of time series signals are difficult to predict as consist of non-linear, high complexity (noise) and chaotic processes. The challenges in time series prediction are to provide a technique to better understand a dataset. In line with this, the Cuckoo Search (CS) learning algorithm, a kind of metaheuristics techniques employs high-level techniques for exploration and exploitation of the search space in which its step length is much longer in the long run. Thus, can explicitly being used to address the possibilities of stochastic trends in time series signals. Since its discovery, the CS has been used extensively. However, these methods fixed the parameter values which essential for adjusting the weights. Therefore, a modification was made by the additional step of information exchange between the top eggs, which significantly improve the convergence rate. Hence, motivated by the advantages of those Modified Cuckoo Search (MCS), the improvement of the MCS called Modified Cuckoo Search-Markov chain Monté Carlo (MCS-MCMC) learning algorithm is proposed for weight optimisation. As the Markov chain Monté Carlo can replace the cumbersome in generating the objective functions, it is used to substitute the Lévy flight found in the MCS's structure to prove that MCS-MCMC is suitable for predictive tasks. The performance of MCS-MCMC learning algorithm was validated with several test functions and compared with those of MCS learning algorithm. The MCS-MCMC results is further benchmarked with the standard Multilayer Perceptron, standard Pi-Sigma Neural Network (PSNN), Pi-Sigma Neural Network-Modified Cuckoo Search, Pi-Sigma Neural Network-Markov chain Monté Carlo, standard Functional Link Neural Network (FLNN), Functional Link Neural Network-Modified Cuckoo Search and Functional Link Neural Network-Markov chain Monté Carlo which emphasis in optimising the accuracy rate. The simulation results proved that MCS-MCMC outperformed in the form of Accuracy with the range of 0.003% to 4.421% when incorporated with standard PSNN and FLNN for three (3) data partitions covering 10 benchmarked time series datasets.

ABSTRAK

Sebilangan besar isyarat siri masa sukar untuk diramal kerana melibatkan proses tidak linear, kerumitan tinggi (kebisingan) dan kekacauan. Cabaran dalam ramalan siri masa adalah menyediakan teknik untuk memahami set data dengan lebih baik. Sejajar dengan ini, algoritma metaheuristik *Cuckoo Search (CS)* menggunakan teknik aras tinggi bagi eksplorasi dan eksploitasi ruang carian di mana panjang langkahnya jauh lebih lama dalam jangka panjang. Hal ini secara eksplisitnya dapat digunakan bagi menangani kemungkinan kecenderungan stokastik dalam isyarat siri masa. Walau bagaimanapun, kaedah ini memalarkan nilai pembolehubah yang diperlukan untuk pengubahsuaian pemberat. Oleh itu, pindaan dilakukan melalui tukaran maklumat antara telur-telur tertinggi, bagi meningkatkan kadar penumpuan secara signifikan. Inspirasi dari kelebihan *Modified Cuckoo Search (MCS)*, penambahbaikan *MCS* yang dikenali sebagai algoritma pembelajaran *Modified Cuckoo Search-Markov chain Monté Carlo (MCS-MCMC)*, dicadangkan untuk pengoptimuman pemberat. Memandangkan *Markov chain Monté Carlo* dapat menggantikan kerumitan dalam menjana fungsi objektif, ia digunakan untuk menyilih *Lévy flight* yang terdapat di dalam *MCS* bagi membuktikan bahawa *MCS-MCMC* sesuai untuk tugas-tugas ramalan. Prestasi *MCS-MCMC* disahkan dengan beberapa fungsi ujian dan dibandingkan dengan algoritma pembelajaran *MCS*. Dapatan *MCS-MCMC* kemudiannya dibandingkan dengan *Multilayer Perceptron (MLP)* piawai, *Pi-Sigma Neural Network (PSNN)*, *Pi-Sigma Neural Network-Modified Cuckoo Search, Pi-Sigma Neural Network-Markov chain Monté Carlo*, *Functional Link Neural Network (FLNN)* piawai, *Functional Link Neural Network-Modified Cuckoo Search* dan *Functional Link Neural Network-Markov chain Monté Carlo* yang menekankan pengoptimuman kadar ketepatan. Dapatan simulasi membuktikan bahawa *MCS-MCMC* mengungguli dalam bentuk Ketepatan dengan julat 0.003% hingga 4.421% apabila digabungkan dengan *PSNN* dan *FLNN* piawai bagi tiga (3) pembahagian data yang meliputi 10 set data siri bertanda masa.

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LIST OF SYMBOLS AND ABBREVIATIONS

NN	-	Neural Networks
RNN	-	Recurrent Neural Networks
HONN	-	Higher Order Neural Networks
PSNN	-	Pi-Sigma Neural Network
FLNN	-	Functional Link Neural Network
PSNN-MCS	-	Pi-Sigma Neural Network-Modified Cuckoo Search
PSNN-MCMC	-	Pi-Sigma Neural Network-Markov chain Monté Carlo
FLNN-MCS	-	Functional Link Neural Network-Modified Cuckoo Search
FLNN-MCMC	-	Functional Link Neural Network-Markov chain Monté Carlo
GA	-	Genetic Algorithm
EA	-	Evolutionary Algorithm
DE	-	Differential Evolution
ABC	-	Artificial Bee Colony
CS	-	Cuckoo Search
ICS	-	Improved Cuckoo Search
MCS	-	Modified Cuckoo Search
MCMC	-	Markov chain Monté Carlo
MCS-MCMC	-	Modified Cuckoo Search-Markov chain Monté Carlo
CPN	-	Counterpropagation Networks
MLP	-	Multilayer Perceptron
BP	-	Backpropagation
SI	-	Swarm Intelligence

PSO	-	Particle Swarm Optimisation
HS	-	Harmony Search
P_{α}	-	Probability
α	-	Step size, real number
c_1, c_2	-	Cognitive and social acceleration factors
$pbest$	-	Personal best
$gbest$	-	Global best
r_1, r_2	-	Random numbers between $(0,1)$
$\Delta\,\omega$	-	Parameters to be optimised
t_{sim}	-	Time range of the simulation
n	-	Number of particles in group, nest, step random walk, number of output nodes in output layer
m	-	Number of members in a particle
t	-	Number of iterations (generations)
$v_{j,g}^{(t)}$	-	Particle velocity j at iteration t
w	-	Inertia weight factor
AI	-	Artificial Intelligence
$x^{(t+1)}$	-	New solutions
$\oplus$	-	Entrywise multiplications
λ	-	Heavy-tailed distributions
NI	-	Number of total iterations
gn	-	Current iteration
φ	-	Golden ratio
A	-	Lévy flight step size, $m \times n$ matrix, data
G	-	Number of generations
x_i	-	Current position, vector of inputs, i^{th} component of x, initial population of n nests
F_i	-	Quality/fitness
x_k	-	New egg

l	-	Random nest
dx	-	Distance
SVM	-	Support Vector Machine
MI	-	Mutual Information
OCS	-	Opposition-Based Cuckoo Search Algorithm
MI-MCS-FWSVM	-	Automatic Detection of Diabetes Diagnosis using Feature Weighted SVM based on MI and MCS
FA	-	Fireworks algorithm
ACO	-	Ant Colony Optimisation
KH	-	Krill herd
QPSO	-	Quantum-behaved PSO
KH-QPSO	-	KH and QPSO
U	-	Survivor function
O	-	Big O notation
D	-	Parameter related to the fractal dimension
h	-	Step of lattice distribution or maximum step
X	-	Distribution span
μ	-	Average number of events per interval, Mean of the normal distribution
Z	-	Random walk on the integer number line
c	-	Trapping point
S	-	Number of distinct sites visited during n step random walk
r	-	Uniformly distributed random number
σ	-	Standard deviations of the normal distribution, inverse cumulative normal distribution, non-linear activation function, non-linear transfer function
v^s	-	Starting value of the random walk
$N(\ )$	-	Notation for the normal distribution
X_i	-	Identically distributed random variables

$s_1, s_2, \ldots s_r$	-	Large number of steps
N	-	Layers in the network, number of expansions for every input, number of elements
w_{ij}	-	Weights
θ	-	Bias, initial value, candidate point
RPNN	-	Ridge-Polynomial Neural Network
d :	-	Set of structures in the group of data
h_{ij}	-	Output if the j^{th} summing units for the k^{th} output
y_k	-	Output
θ_{ij}	-	Tuneable coefficients
O_k	-	Network output of the k^{th} output unit
t_k	-	Desired output of the k^{th} output unit
E_i	-	Minimum of the error function
i	-	Node
s_c	-	Real function
c	-	Constant
f	-	Primitive function
f_0	-	Derivative on the left
x_1, x_2	-	Independent variables
$F(x_1, x_2)$	-	Network result
o_i	-	Stored output
$\frac{\partial E_i}{\partial w_{ij}}$	-	Partial derivative of E_i with respect to w_{ij}
Δw_{ij}	-	Increment to each weight w_{ij}
$f_1(x)$	-	Ackley Test Function
$f_2(x)$	-	Rosenbrock Test Function
$f_3(x,y)$	-	Bohachevsky Test Function
$f_4(x,y)$	-	Matyas Test Function

$f_5(x,y)$	-	Booth Test Function
$f_6(x,y)$	-	Three-Hump Camel Test Function
$f_7(x)$	-	Eggholder Test Function
$f_8(x,y)$	-	Himmelblau Test Function
$f_9(x,y)$	-	Schaffer N. 2 Test Function
$f_{10}(x)$	-	Schaffer N. 4 Test Function
$f_{11}(x)$	-	Styblinski-Tang Test Function
$f_{12}(x)$	-	Rastrigin Test Function
$f_{13}(x,y)$	-	Schwefel Test Function
$f_{14}(x,y)$	-	McCormick Test Function
$f_{15}(x,y)$	-	Six-Hump Camel Test Function
JPEU	-	Japanese Yen to Euro
JPUK	-	Japanese Yen to UK Pound
JPUS	-	Japanese Yen to US Dollar
B	-	Reshape matrix
min A	-	Minimum values of the data A
max A	-	Maximum values of the data A
v'	-	Normalised value
v	-	Observation value
CLT	-	Central limit theorem
PDF	-	Probability density function
$p(\theta)$	-	PDF
n	-	Target PDF parameter, Total number of data patterns
P	-	Density ratio
θ_{t-1}	-	Current points
η	-	Learning rate
θ^*	-	Candidate value
x_1, x_2 and x_3	-	Inputs
w_0	-	Adjustable threshold
y	-	Output node

$f(x)$	-	Sigmoid function
x	-	Sigmoid's midpoint
MSE	-	Mean Squared Error
RMSE	-	Root Mean Squared Error
P_i	-	Actual output value
$\tilde{P}_i$	-	Predicted output value
$f(x)$	-	Objective function
x_i, x_j, x_k	-	Input vector
w_{ijk}	-	Adjustable weight
e	-	Error tolerance
$x_1, x_2, \ldots x_n$	-	Input units
$h_1, h_2, \ldots h_l$	-	Summing units
$\overline{x}$	-	Mean of x_i
x^*	-	Global minimum
d	-	Dimension
$Improvement_c$	-	Improvement for PSNN-MCMC
$Improvement_f$	-	Improvement for FLNN-MCMC

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LIST OF PUBLICATIONS

(i) Noor Aida Husaini, Rozaida Ghazali, Lokman Hakim Ismail, Nureize Arbaiy and Habib Shah (2020). “A Modified Cuckoo Search-Markov Chain Monte Carlo: The Alternative Gradient Free Optimisation Algorithm.” International Journal of Advanced Trends in Computer Science and Engineering Advanced Trends in Computer. Vol. 9, No. 1.1, pp. 550-559.

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(iii) Noor Aida Husaini, Rozaida Ghazali, and Iwan Tri Riyadi Yanto (2016). “Enhancing Modified Cuckoo Search Algorithm by using MCMC Random Walk.” 2nd International Conference on Science in Information Technology (ICSITech), pp. 306-311. IEEE.

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